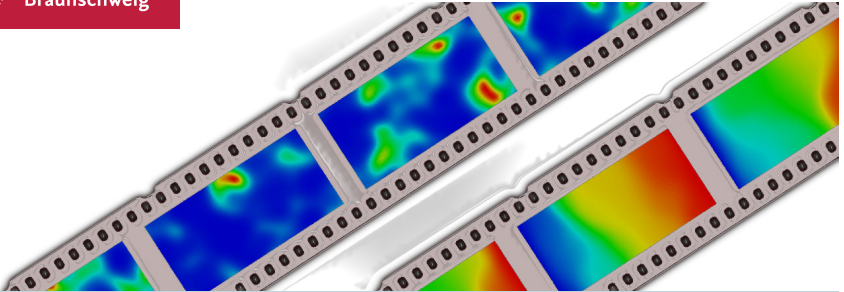
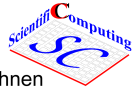




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Successive Rank-One Updates and an Adaptive Construction of the Solution Space

*Presentation in the course “Uncertainty Quantification, Parametric Problems,
and Model Reduction” (INF-WR-014)*

Martin Krosche, 4th July 2014

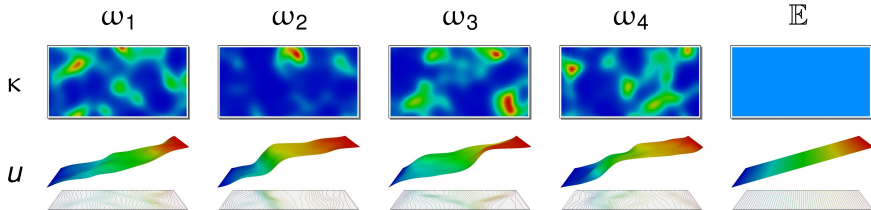
Content

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Stationary Groundwater Flow

$$-\nabla_{\mathbf{X}} \cdot (\kappa(\mathbf{x}, \omega) \nabla_{\mathbf{X}} u(\mathbf{x}, \omega)) = f(\mathbf{x})$$

- $\mathbf{x} \in X \subset \mathbb{R}^2$, $\omega \in \Omega$, $\mathcal{P} := (\Omega, \mathcal{F}, P)$
- hydraulic conductivity $\kappa : X \times \Omega \rightarrow \mathbb{R}$
- uncertain $\kappa \Rightarrow$ uncertain hydraulic head $u : X \times \Omega \rightarrow \mathbb{R}$



Discretisation of a Random Field

$$\nu(\mathbf{x}, \omega) \approx \nu_h(\mathbf{x}, \omega) := \sum_{i \in \{1, \dots, N_X\}, j \in \{1, \dots, N_S\}} \nu_{i,j} \phi_i(\mathbf{x}) \psi_j(\omega) = \boldsymbol{\Phi}(\mathbf{x})^T \mathbf{V} \boldsymbol{\Psi}(\omega)$$

$$\mathbf{V} := \begin{pmatrix} \nu_{1,1} & \cdots & \nu_{1,N_S} \\ \vdots & \ddots & \vdots \\ \nu_{N_X,1} & \cdots & \nu_{N_X,N_S} \end{pmatrix}$$

spatial basis functions $\boldsymbol{\Phi} := (\phi_1, \dots, \phi_{N_X})^T$

stochastic basis functions $\boldsymbol{\Psi} := (\psi_1, \dots, \psi_{N_S})^T$

- e.g. polynomial chaos expansion (PCE):

$$\psi_i(\omega) := \psi_i(\boldsymbol{\theta}(\omega)), \quad \psi_i \perp \psi_j \quad (i \neq j)$$

- \mathbf{V} may become large \Rightarrow sparsification of $\boldsymbol{\Psi}$?
low-rank representation of \mathbf{V} ?

A Low-Rank Representation of a Random Field

$$v_h(\mathbf{x}, \omega) := \Phi(\mathbf{x})^T \mathbf{V} \Psi(\omega)$$

$$\approx v_h^r(\mathbf{x}, \omega) := \Phi(\mathbf{x})^T \left[\sum_{i=1}^r \mathbf{g}_i \mathbf{h}_i^T \right] \Psi(\omega) = \Phi(\mathbf{x})^T \mathbf{G} \mathbf{H}^T \Psi(\omega)$$

$$\mathbf{G} \in \mathbb{R}^{N_X \times r}, \quad \mathbf{H} \in \mathbb{R}^{N_S \times r}, \quad r \ll \min\{N_X, N_S\}$$

- reduction of memory requirements
- more efficient computational handling
- e.g. Karhunen-Loève expansion (KLE)

Stochastic Galerkin Method (SGM): Discretisation

A stationary groundwater flow:

$$-\nabla_{\mathbf{x}} \cdot (\kappa(\mathbf{x}, \omega) \nabla_{\mathbf{x}} u(\mathbf{x}, \omega)) = f(\mathbf{x})$$

Discretising the weak form by

$$u_h(\mathbf{x}, \omega) := (\boldsymbol{\psi}(\omega) \otimes \boldsymbol{\phi}(\mathbf{x}))^T \mathbf{u} = \boldsymbol{\phi}(\mathbf{x})^T \mathbf{U} \boldsymbol{\psi}(\omega) \quad (\text{PCE+FE})$$

leads to a linear system (to be solved):

$$\boxed{\left(\sum_{i=1}^I \Delta_i \otimes \mathbf{K}_i \right) \mathbf{u} = \mathbf{f}} \iff \boxed{\sum_{i=1}^I \mathbf{K}_i \mathbf{U} \Delta_i = \mathbf{F}} \iff \boxed{\mathbf{A}(\mathbf{U}) = \mathbf{F}}$$

$\mathbf{u}, \mathbf{f} \in \mathbb{R}^{N_x \cdot N_s}$ $\mathbf{U}, \mathbf{F} \in \mathbb{R}^{N_x \times N_s}$

Successive Rank-1 Updates

Proper Generalised Decomposition (PGD):

- low-rank representation through successive rank-1 updates:
rank-one update $\mathbf{U} = \mathbf{U}^- + \mathbf{g}\mathbf{h}^T = \mathbf{G}^-(\mathbf{H}^-)^T + \mathbf{g}\mathbf{h}^T$
- locally optimal (greedy)
- not necessarily globally optimal
- not necessarily orthogonal rank-1 updates

Successive Rank-1 Update Scheme (SR1U):

- successive rank-1 updates similar to PGD (greedy)
- optimisation to obtain globally optimal representation (optional)
- not necessarily orthogonal rank-1 updates
- adaptive construction of the stochastic solution space (optional)

Successive Rank-1 Update Scheme (SR1U)

Minimisation of the expectation of the total potential energy:

$$\mathcal{A}(\mathbf{U}) = \mathbf{F}$$

$$\iff \mathcal{E}(\mathbf{U}) := \frac{1}{2} \mathcal{A}(\mathbf{U}) : \mathbf{U} - \mathbf{F} : \mathbf{U} \longrightarrow \min$$

$$\text{with } A : B := \sum_{i,j} A_{ij} B_{ij}, \quad A, B \in \mathbb{R}^{n_1 \times n_2}$$

Ansatz:

$$\mathbf{U} = \mathbf{U}^- + \mathbf{g}\mathbf{h}^T$$

(locally optimal rank-1 update)

spatial part \mathbf{g}

stochastic part \mathbf{h}

SR1U: Derivation

Differentiating $\mathcal{E}(\mathbf{U})$ with respect to \mathbf{U} and...

- differentiating \mathbf{U} with respect to \mathbf{g} leads to (spatial system)

$$\mathbf{P}(\mathbf{h}) \mathbf{g} = \mathbf{b}(\mathbf{h})$$

- differentiating \mathbf{U} with respect to \mathbf{h} leads to (stochastic system)

$$\mathbf{Q}(\mathbf{g}) \mathbf{h} = \bar{\mathbf{b}}(\mathbf{g})$$

- alternating iterative process

Output:
$$\mathbf{U} := \sum_{i=1}^r \mathbf{g}_i \mathbf{h}_i^T = \mathbf{G} \mathbf{H}^T$$

SR1U: Algorithm

```

1:  $\mathbf{H} \leftarrow \emptyset, \quad \mathbf{G} \leftarrow \emptyset$ 
2: while break criterion not reached do
3:      $\mathbf{h} \leftarrow \text{rand}, \quad \mathbf{g} \leftarrow \mathbf{0}$ 
4:     while break criterion not reached do
5:          $\mathbf{h} \leftarrow \text{normalise } \mathbf{h}$ 
6:          $\mathbf{g} \leftarrow \text{solve } \mathbf{P}(\mathbf{h}) \mathbf{g} = \mathbf{b}(\mathbf{h})$ 
7:          $\mathbf{g} \leftarrow \text{normalise } \mathbf{g}$ 
8:          $\mathbf{h} \leftarrow \text{solve } \mathbf{Q}(\mathbf{g}) \mathbf{h} = \bar{\mathbf{b}}(\mathbf{g})$ 
9:     end while
10:     $\mathbf{G} \leftarrow [\mathbf{G}, \mathbf{g}]$ 
11:     $\mathbf{H} \leftarrow [\mathbf{H}, \mathbf{h}]$ 
12: end while

```

SR1U: Solving the Spatial System

$$\boxed{\mathbf{P}(\mathbf{h}) \mathbf{g} = \mathbf{b}(\mathbf{h})} \quad \text{with} \quad \mathbf{P}(\mathbf{h}) := \sum_{i=0}^l \underbrace{\mathbf{h}^T \Delta_i \mathbf{h}}_{=: d_i(\mathbf{h})} \mathbf{K}_i,$$

$$\mathbf{b}(\mathbf{h}) := (\mathbf{F} - \mathcal{A}(\mathbf{U}^-)) \mathbf{h}$$

If $\mathbf{K}_i := \mathbf{K}(\kappa_i)$ is **linear** in its material κ_i the computational costs can be reduced:

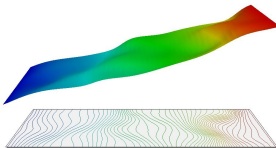
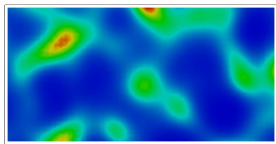
$$\mathbf{P}(\mathbf{h}) := \sum_{i=0}^l d_i(\mathbf{h}) \mathbf{K}(\kappa_i) = \boxed{\mathbf{K}(\sum_{i=0}^l d_i(\mathbf{h}) \kappa_i)}.$$

Then, the spatial system may be solved by a simulation code for deterministic models.

SR1U: Stationary Groundwater Flow

Discretisation:

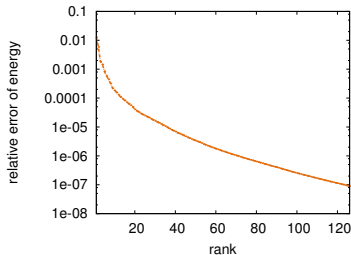
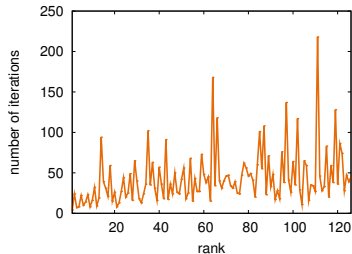
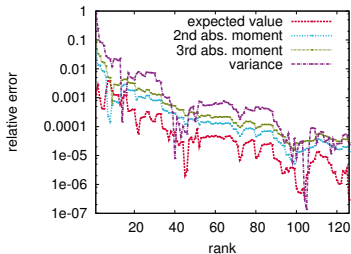
- 5 stochastic dimensions
- 126 stochastic DoFs
- 231 spatial DoFs



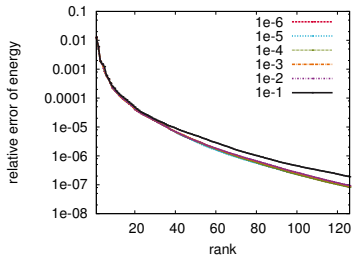
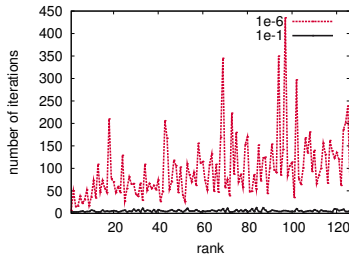
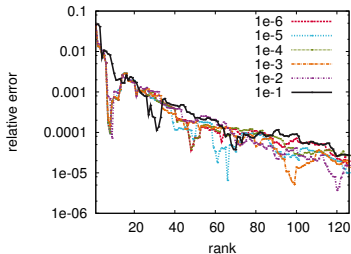
Reference:

- direct solution of the SGM-discretised system

SR1U: Stationary Groundwater Flow (2)



SR1U: Stationary Groundwater Flow (3)



SR1U: Low-Rank Optimisation (OPT)

Improve computed low-rank approximation:

Apply the SR1U scheme onto projections of $\mathcal{A}(\mathbf{U}) = \mathbf{F}$

$$\begin{aligned}\mathcal{A}(\mathbf{U})\mathbf{H} &= \mathbf{F}\mathbf{H} \\ \mathbf{G}^T\mathcal{A}(\mathbf{U}) &= \mathbf{G}^T\mathbf{F}\end{aligned}$$

to obtain rank-1 updates

$$\begin{aligned}\mathbf{G} &= \mathbf{G}^- + \mathbf{g}\mathbf{v}^T = \mathbf{G}^- + \Delta\mathbf{G} \\ \mathbf{H} &= \mathbf{H}^- + \mathbf{h}\mathbf{w}^T = \mathbf{H}^- + \Delta\mathbf{H}\end{aligned}$$

- a coupled system for each update
- updates without a rank increase for $\mathbf{U} = \mathbf{G}\mathbf{H}^T$

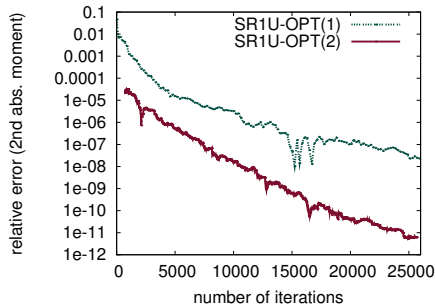
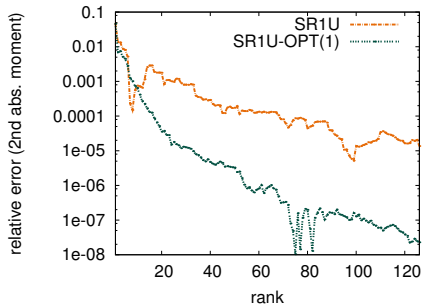
OPT: Algorithm

- 1: $\mathbf{G} \leftarrow \mathbf{G}^-$, $\mathbf{H} \leftarrow \mathbf{H}^-$
- 2: **while** break criterion not reached **do**
- 3: $\mathbf{g}, \mathbf{v} \leftarrow$ get rank-1 update for \mathbf{G}
- 4: $\mathbf{G} \leftarrow \mathbf{G} + \mathbf{g}\mathbf{v}^T$
- 5: $\mathbf{h}, \mathbf{w} \leftarrow$ get rank-1 update for \mathbf{H}
- 6: $\mathbf{H} \leftarrow \mathbf{H} + \mathbf{h}\mathbf{w}^T$
- 7: **end while**

- accepts arbitrary low-rank inputs
- embedded in the SR1U scheme:
 - on the fly (SR1U-OPT-1)
 - as a post-processor (SR1U-OPT-2)

SR1U-OPT: Stationary Groundwater Flow

Optimise $U = G H^T$:



Adaptive Choice of Stochastic Basis Polynomials

Given: $\mathbf{U} \leftarrow \sum_{i=0}^l \mathbf{K}_i \mathbf{U} \Delta_i = \mathbf{F}$

- \mathbf{U} is not accurate enough?
- extend the solution space by relevant stochastic polynomials
- recompute \mathbf{U}

How to find relevant stochastic polynomials?

- add new stochastic polynomials ψ^+ : $\Delta_i^\oplus := \left(\begin{array}{c|c} \Delta_i & \Delta_i^\triangleleft \\ \hline \Delta_i^\triangleright & \Delta_i^+ \end{array} \right)$
- compute the extended residual with current solution \mathbf{U}
 $\mathbf{R}^\oplus := \mathbf{F}^\oplus - \sum_{i=0}^l \mathbf{K}_i \mathbf{U} \Delta_i^\uplus$ with $\Delta_i^\uplus := [\Delta_i, \Delta_i^\triangleleft]$
- rate the new stochastic polynomials and keep the best rated ones

SR1U-ADAPT: Adaptive Solution Space Construction

Embedding in the SR1U scheme:

Inout: ψ

1: **if** solution space not fine enough **then**

2: select ψ^+

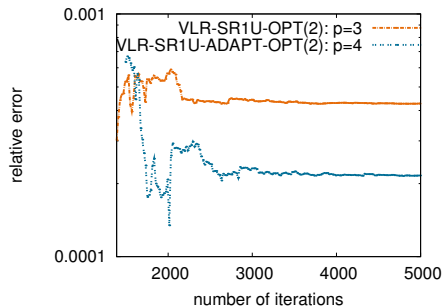
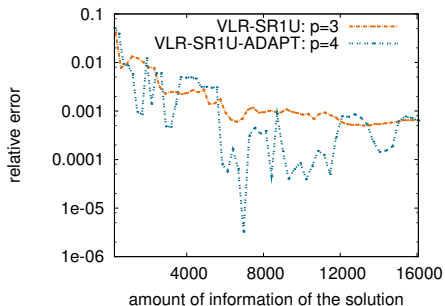
3: $\hat{\psi} \leftarrow \text{rate } \psi^+$

4: $\psi \leftarrow [\psi, \hat{\psi}]$

5: **end if**

- use the extended solution space for the next rank-1 updates
- one optimisation step takes the previous rank-1 updates to the extended solution space
- no recomputation of \mathbf{U} required

SR1U-ADAPT: Stationary Groundwater Flow



SR1U: Intermediate Conclusions

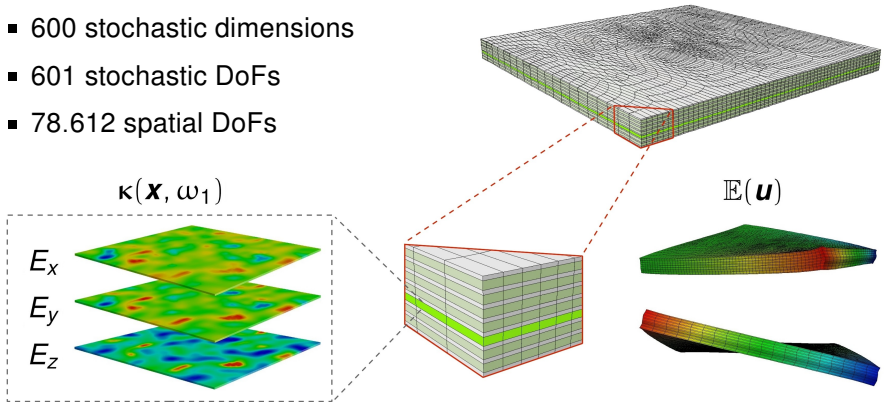
- computational advantage when the stiffness matrix is linear in its material
- few iterations are enough to obtain an accurate rank-1 update
- an optimisation on the fly is less efficient than an optimisation at a final rank
- the residual-based adaption of the stochastic solution space is promising

Laminated Composite Structure with a Linear Constitutive Law

$$\kappa : X \times \Omega \rightarrow \mathbb{R}^{21}, \quad \mathbf{u} : X \times \Omega \rightarrow \mathbb{R}^3$$

Discretisation:

- 600 stochastic dimensions
- 601 stochastic DoFs
- 78.612 spatial DoFs

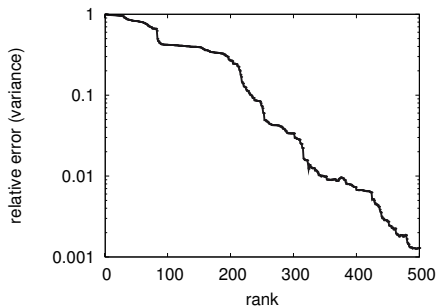


SR1U: Laminated Composite Structure

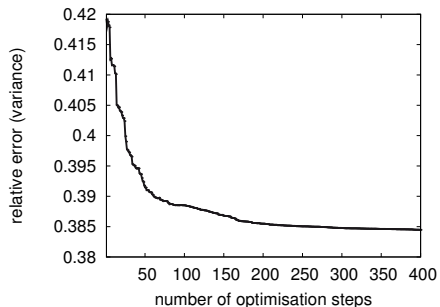
Reference:

- full rank representation (SR1U)

SR1U:



OPT-2 at rank 100:



Summary

Successive rank-1 update scheme:

- in its basic form suboptimal
- optimisation of rank- r solutions
- construction of a sparse stochastic solution space
- convergence for simple and difficult examples

Related Publications:

Martin Krosche. *A Generic Component-Based Software Architecture for the Simulation of Probabilistic Models*. PhD thesis, Technische Universität Braunschweig, Braunschweig, 2013. <http://www.digibib.tu-bs.de/?docid=00052792>.

Martin Krosche and Rainer Niekamp. Low rank approximation in spectral stochastic finite element method with solution space adaption. Informatikbericht 2010–03, Institut für Wissenschaftliches Rechnen, Technische Universität Braunschweig, Braunschweig, 2010. <http://www.digibib.tu-bs.de/?docid=00036351>.

Outlook

Successive rank-1 update scheme:

- improve initial guesses for rank-1 updates
- automatic control of rank-1 updates and solution space adaptations
- application to nonlinear problems